



Contents lists available at **ETG**

Emerging Technologies and Governance

Journal homepage: www.etg.ihu.ac.ir



AI-Enabled Robust Performance-Based Budgeting: A Hybrid Neural–Optimization Approach for Smart Governance

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<https://doi.org/10.47176/ETG.2026.1005>

ARTICLE INFO

Article history:

Received: 11 September 2025

Revised: 29 November 2025

Accepted: 14 December 2026

Keywords:

Smart Governance;

AI-Enabled Budgeting;

Performance-Based Budgeting;

Robust Optimization;

Artificial Neural Network.

ABSTRACT

Performance-based budgeting (PBB) remains one of the most critical challenges in modern public expenditure management, particularly as governments transition toward data-driven and intelligent governance systems. Advances in artificial intelligence now allow budgeting processes to move beyond subjective estimates and toward analytical, transparent, and evidence-based decision-making. This study introduces an AI-enabled hybrid framework for PBB that integrates Artificial Neural Networks (ANN) with robust linear optimization to support smart governance and resilient resource allocation. The ANN component learns complex cost–activity relationships from historical organizational data and generates predictive estimates for future costs and cost drivers, which are among the primary sources of uncertainty in budgeting. These ANN-derived uncertainty intervals are then incorporated into a robust optimization model following Soyster and Bertsimas–Sim formulations to ensure both feasibility and optimality under uncertain conditions. The proposed hybrid model provides a transparent and intelligence-driven mechanism for allocating resources in alignment with organizational goals. The framework is validated within a major Iranian bank. Empirical results demonstrate that integrating ANN-based cost estimation with robust optimization significantly improves budget deviation indicators and enhances the accuracy, stability, and resilience of the budgeting process. The study contributes to the evolving field of smart governance by presenting a mathematically rigorous, AI-enhanced, and uncertainty-aware budgeting methodology.

How to cite this article: Khadivar, A., & Saba, A. (2026). AI-Enabled Robust Performance-Based Budgeting: A Hybrid Neural–Optimization Approach for Smart Governance. *Emerging Technologies and Governance*, 1(1), 41–65.

ISSN-ISSN/ © 2026 The Authors. Published by Imam Hossein University.

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1. Introduction

Rapid developments in information technology, data-centric approaches, and artificial intelligence have opened new horizons in governance and public management. Smart and inclusive governance emphasizes transparency, accountability, efficiency, and data-driven decision-making while supporting sustainability ([Al Mokdad, 2025](#)). AI-driven intelligent governance represents a new paradigm for adaptive and data-informed decision-making in public administration ([He et al., 2025](#)). Technological innovations have increasingly enhanced transparency and accountability in public sector budgeting, supporting more informed and effective resource allocation ([Paul](#)). Furthermore, AI-based approaches provide new opportunities for ethical, resilient, and intelligent governance frameworks ([Vadisetty, 2024](#)).

Within this context, budgeting and resource allocation can no longer rely solely on historical expenditures or traditional demand patterns; resources must be allocated based on tangible results, measurable outputs, and quantitative and qualitative indicators. Performance-Based Budgeting (PBB) precisely addresses this objective: it seeks to link allocated funds to actual organizational outcomes using systematic performance information, thereby enhancing transparency, accountability, and efficiency ([Curristine, 2005](#); [McNab & Melese, 2003](#); [Zafar, 2008](#)). In the 1990s, a renewed wave of interest in performance budgeting emerged across governments, and since then, the adoption of PBB has steadily increased. Historical budgeting approaches include additive budgeting, program budgeting, Planning–Programming–Budgeting (PPB) systems, Zero-Based Budgeting (ZBB), and the first generation of performance budgeting, each with varying levels of success ([Shah & Shen, 2007](#)). Mathematical models have also played a key role in budgeting research, allowing analysts to formalize allocation structures and optimize their financial decisions. Examples include the PPB system of Charnes and Cooper ([Charnes & Cooper, 1971](#)), ZBB mathematical models ([Lee & Shim, 1984](#)), linear programming for cash planning ([Charnes et al., 1959](#)), Burton’s short-term and long-term budgeting models ([Burton, 1979](#)), national budgeting models such as for the Nigerian economy ([Habeeb, 1991](#)), multi-criteria public sector allocation models ([Greenberg & Nunamaker, 1994](#)), goal programming approaches ([Zanakis, 1991](#)), and deterministic or fuzzy cost allocation models applied in Iranian governmental organizations ([Azar, 1999](#)). Following the restoration and modernization of the PBB in the 1990s, the complexity of resource allocation increased ([Curristine, 2007](#)). Numerous interdependent parameters, including cost drivers, activity volumes, performance indicators, and operational constraints, render purely qualitative or subjective approaches insufficient for achieving optimal budget decisions. Mathematical modeling provides a structured alternative; however, most models assume deterministic parameters, whereas in practice, parameters are uncertain, and deviations from nominal values may render previously optimal solutions suboptimal or infeasible ([Mulvey et al., 1995](#)). In PBB, many parameters, particularly cost drivers and projected future costs, are inherently uncertain and must be estimated using incomplete or noisy data ([Babad & Balachandran, 1993](#); [Kim & Han, 2003](#)). Furthermore, managers require flexibility and the ability to adjust parameters under real-world conditions. To address these uncertainties, robust optimization is employed to ensure that resource allocations remain feasible and near-optimal across different scenarios. In this paper, we propose a hybrid linear programming model for PBB. Its primary variables represent activity volumes and performance rather than cash allocations, and

its coefficients are derived from cost drivers estimated using an Artificial Neural Network (ANN). Subsequently, two robust optimization models based on Soyster's method and the Bertsimas–Sim adjustable robustness approach were developed to maintain feasibility and optimality under uncertainty. We argue that this combination of smart governance principles, PBB, and data-driven quantitative modeling represents an important step toward responsive, transparent, and flexible budgeting systems that can achieve public policy objectives more efficiently and equitably than the traditional approach. The remainder of this paper is organized as follows: Section 2 reviews the relevant literature; Section 3 introduces the proposed hybrid model; Sections 4 and 5 describe the experimental procedures and results, respectively; and Section 6 presents the discussion, conclusions, limitations, and directions for future research.

2. Literature Review

2.1. Performance-Based Budgeting and Smart Governance in Public Administration

Performance-Based Budgeting (PBB) is a central approach in public management that links allocated resources to measurable outputs and outcomes ([Curristine, 2005](#); [McNab & Melese, 2003](#); [Zafar, 2008](#)). Although its roots trace back to the early 20th century, PBB was formally introduced in the 1940s as an alternative to traditional input-based budgeting methods. Various terms—including budgeting for results, performance-based budgeting, and performance funding—highlight the integration of performance information into budgetary decisions ([De Vries & Nemec, 2019](#)).

PBB emphasizes activity-based budgeting, connecting resources to program activities and goals rather than solely focusing on material costs. Its key components include workload data, productivity metrics and effectiveness indicators ([Abbasov, 2025](#)). The revival of PBB in the 1990s was motivated by prior system inefficiencies, the maturity of performance measurement, simplicity of use, and greater attention to accountability ([Curristine, 2007](#); [Islam, 2025](#)).

Recent developments in smart governance and AI have enhanced PBB by enabling data-driven, transparent, and flexible budgeting processes ([Al Mokdad, 2025](#); [Barsekh-Onji et al., 2025](#); [He et al., 2025](#); [Vadisetty, 2024](#) {[Barsekh-Onji, 2025](#) #13}). Digital transformation and smart public administration tools improve policy effectiveness, resource allocation, and organizational responsiveness (Saim & Traore, 2025; Fedchenko et al., 2025; Islam, 2025). Integrating AI, predictive analytics, and smart control models strengthens financial management under uncertainty, bridging the gap between traditional budgeting practices and modern governance requirements ([Abbasov, 2025](#); [De Vries & Nemec, 2019](#)).

2.2. Mathematical Models of Budgeting

Mathematical models play a central role in formalizing budgeting systems and optimizing resource allocation. The PPBS system ([Charnes & Cooper, 1971](#)) introduced a hierarchical structure linking central, middle, and operational units for planning and resource distribution in the public sector. Zero-Based Budgeting (ZBB) ([Lee & Shim, 1984](#)) organizes decisions as packages, including

activities, resources, and goals, and incorporates constraints for program objectives, minimum utility, and budget limits.

Linear and nonlinear programming models have been widely applied for short- and long-term budgeting, considering production, financial, and marketing variables ([Baker & Damon, 1977](#); [Burton, 1979](#); [Charnes et al., 1959](#)). Multi-criteria goal programming and AHP-based models enable optimal budget allocation in complex public-sector projects ([Greenberg & Nunamaker, 1994](#); [Zanakis, 1991](#)). Fuzzy models address uncertainty in cost estimates and planning ([Azar, 1996, 1999](#)), and objective models have been applied to national economies such as Nigeria ([Habeeb, 1991](#)).

Other studies have focused on costing, planning, and performance evaluation, including ABC, optimization of cost drivers, and robust approaches for uncertain data ([Bienstock & Shapiro, 1988](#)) ([Babad & Balachandran, 1993](#); [Balachandran et al., 1997](#); [Homburg, 2004](#); [Schniederjans & Garvin, 1997](#)). Despite extensive research, comprehensive mathematical models for Performance-Based Budgeting (PBB) that integrate uncertainty, multi-criteria objectives, and modern AI-based methods remain limited ([Andres et al., 2008](#); [Arora & Klabjan, 2002](#); [Cook, 1984](#); [Drake, 1983](#); [Gleenson & Ottensmann, 1993](#); [Hannan, 1991](#); [Mao, 1969](#); [Niemeyer et al., 1993](#); [Ruefli, 1984](#); [Wise & Perushek, 1996](#); [Yu Ting et al., 2008](#); [Zilla, 1984](#)).

Recent developments in smart governance, AI, and digital transformation have further enhanced budgeting models, improving transparency, accountability, and policy effectiveness ([Abbasov, 2025](#); [Al Mokdad, 2025](#); [Barsekh-Onji et al., 2025](#); [De Vries & Nemec, 2019](#); [Fedchenko et al., 2025](#); [He et al., 2025](#); [Islam, 2025](#); [Saim & Traore, 2025](#); [Vadisetty, 2024](#)). With the emergence of computational methods, quantitative modeling has also been influenced, and these approaches have gained attention as alternative or complementary tools for improving traditional mathematical budgeting models.

2. 3. Robust optimization

ignoring the uncertainty effects on optimality and feasibility. Deviations from the nominal values can violate constraints, making the optimal solution infeasible ([Bienstock & Shapiro, 1988](#)). Even minor fluctuations in uncertain coefficients can endanger solution feasibility with a significant probability ([Ben-Tal et al., 2006](#); [Ben-Tal & Nemirovski, 1998](#)). This motivates the design of robust optimization approaches that aim to find solutions that remain feasible and near-optimal under uncertain conditions.

Robust optimization methods seek solutions that are close to the nominal optimum while ensuring high-probability feasibility, even in worst-case scenarios ([Bertsimas & Sim, 2004](#)). Key approaches include:

1. [Soyster \(1973\)](#) Model – Assumes uncertain constraint coefficients vary independently within known symmetric intervals. Although highly conservative, it guarantees feasibility for all parameter variations.

2. Ben-Tal & Nemirovski's Model ([Ben-Tal et al., 2006](#); [Ben-Tal & Nemirovski, 1998](#)) – Uses ellipsoidal uncertainty sets for constraint coefficients, balancing robustness and optimality, and reducing over-conservatism compared to Soyster's method.

3. [Bertsimas and Sim \(2004\)](#) Model – Introduces protection parameters to control the conservatism level in both constraints and objective function coefficients, providing a flexible framework for linear and discrete optimization under uncertainty.

Other approaches combine robust optimization with goal programming and scenario analysis to simultaneously handle multiple objectives and parameter uncertainties ([El Ghaoui et al., 1998](#); [Mulvey et al., 1995](#)).

Robust optimization is particularly relevant for Performance-Based Budgeting (PBB), where uncertainty in cost drivers, activity volumes, and future expenditures can significantly affect optimal allocation decisions. By integrating robust optimization, budget models can maintain feasibility and near-optimality under uncertain conditions, providing decision-makers with reliable and flexible resource allocation tools.

2.4. AI-enabled Performance based budgeting

Performance-Based Budgeting (PBB) has become a central tool in modern public financial management, linking allocated resources to measurable outcomes while enhancing transparency, accountability, and effectiveness ([Abbasov, 2025](#) ; [De Vries & Nemec, 2019](#); [Islam, 2025](#)). AI techniques, including machine learning, artificial neural networks (ANN), and predictive analytics, enable the accurate forecasting of costs, activity volumes, and performance indicators, supporting dynamic, evidence-based, and adaptive budgeting decisions ([Okafor et al., 2023](#); [Thirunagalingam et al., 2025](#)).

Machine learning methods, such as artificial neural networks (ANNs), decision trees, support vector machines (SVMs), reinforcement learning, and genetic algorithms (GAs), can be applied in various aspects of performance-based budgeting, including activity cost prediction, resource allocation under uncertainty, real-time performance monitoring, and identification of deviations and corrective actions ([Agrawal et al., 2025](#); [Talab & Hijab, 2024](#); [Thirunagalingam et al., 2025](#)).

Integrating AI with robust optimization methods ensures that resource allocation remains feasible and near-optimal, even under uncertainty, thereby improving the reliability and responsiveness of budgetary decisions ([Bertsimas & Sim, 2004](#); [Mulvey et al., 1995](#)). These AI-enabled approaches allow real-time monitoring, adaptive planning, and better alignment of resources with organizational goals, providing a modern framework for smart, resilient, and data-driven public financial management.

Furthermore, Sadeghi Askari et al. (2020) demonstrated that combining artificial neural networks with multilayer data envelopment analysis (DEA) in activity-based costing enables the precise estimation of cost–activity functions in financial organizations. This methodology provides a strong foundation for integrating AI techniques into performance-based budgeting. Table 1 demonstrates the applications of Machine learning in performance-based budgeting.

Table 1.

Applications of machine learning in performance-based budgeting.

No.	Machine Learning / AI Method	Application in Performance-Based Budgeting	References
1	Artificial Neural Networks (ANN)	Forecasting costs and activities; estimating cost–activity functions in Activity-Based Costing; program performance evaluation	(Agrawal et al., 2025 ; Thirunagalingam et al., 2025)
2	Decision Trees	Identifying key factors affecting organizational performance; allocating resources based on priorities	(Okafor et al., 2023 ; Talab & Hijab, 2024 ; Thirunagalingam et al., 2025 ; Vadisetty, 2024)
3	Support Vector Machines (SVMs)	Classifying projects and programs based on risk and budget efficiency	(Agrawal et al., 2025 ; Al Mokdad, 2025 ; Li, 2024 ; Thirunagalingam et al., 2025)
4	Reinforcement Learning	Optimizing resource allocation under uncertainty; learning long-term budgeting policies	(Li, 2024 ; Okafor et al., 2023 ; Talab & Hijab, 2024 ; Thirunagalingam et al., 2025)
5	Genetic Algorithms (GAs)	Optimizing the combination of resources and activities to maximize budget efficiency	(Kim & Han, 2003 ; Thirunagalingam et al., 2025)
6	Predictive Analytics	Forecasting activity volumes, costs, and performance indicators for dynamic and responsive decision- making	(Agrawal et al., 2025 ; Li, 2024 ; Okafor et al., 2023 ; Talab & Hijab, 2024 ; Thirunagalingam et al., 2025)
7	Multi-layer Data Envelopment Analysis + ANN	Evaluating efficiency of programs and units; identifying deviations and improving resource allocation	(Agrawal et al., 2025 ; Azar & Khadivar, 2012 ; Thirunagalingam et al., 2025 ; Vadisetty, 2024)

3. Proposed Model

3.1. Model structure definition

The performance-based budgeting process begins with planning. In this stage, communications of organizational macro goals and strategies to operational objectives and action plans are known in the form of hierarchical relationships and are extracted as a cascade (tree) of planning. In the next

stage, we must cover the costing process to understand the final price of each outcome. This process involves defining activities, products, cost drivers, costs (direct and indirect), and their relationships, and calculating the final cost of activities for every output (product) based on multiple drivers ([Cooper, 1991](#); [Kaplan & Cooper, 1998](#)). In this study, we use the concepts of the ABC model for costing.

During the performance evaluation process, the activities and outputs (products) were evaluated based on the defined Key Performance Indicators. These indicators may be related to financial or non-financial factors. The budget allocated for each item is affected by the results of the performance evaluation ([Curristine, 2005](#); [Zaltsman, 2009](#)).

To formulate a budget, first, resources (the very costs) are predicted for the upcoming budgeting term (future costs). Then, with respect to the final estimated cost for each activity or product and the amount of their use of resources (value of cost drivers) and the amount of their influence on achieving final goals (which will be acquired from performance index evaluation), the optimum volume of activities and outputs for the future will be obtained by solving an Lp model. Finally, the budget of each activity, output (product), and action plan will be calculated based on their optimum volume and final price ([Kim & Han, 2003](#); [Kong, 2005](#); [McNab & Melese, 2003](#); [Zafar, 2008](#)) ([Gilmour & Lewis, 2005](#); [Kamil Tugen, 2010](#); [Lu, 1998](#)). Fig. 1 shows the relationships between the variables of the explained structure.

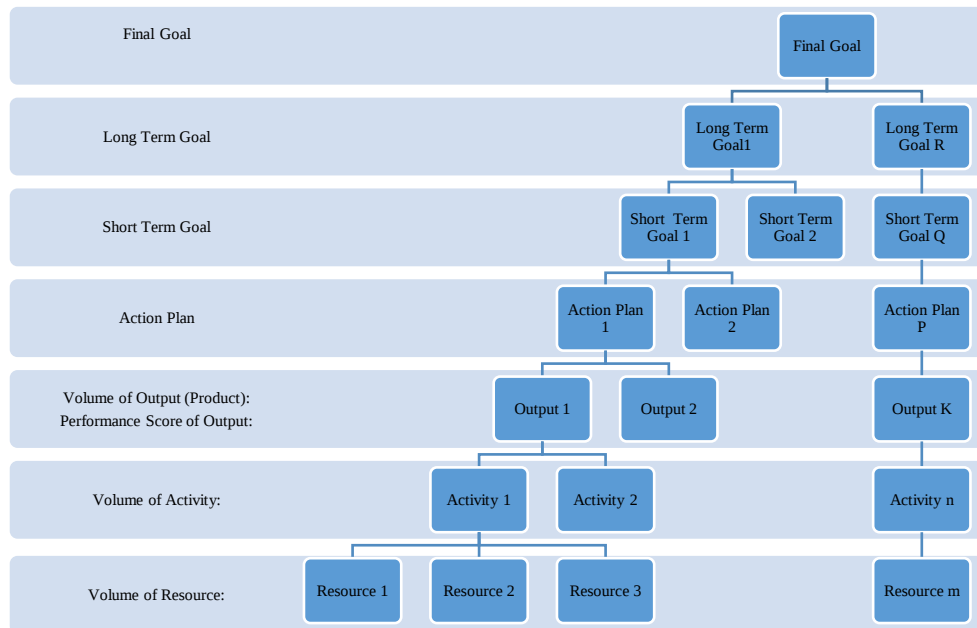


Fig. 1. Performance-based budgeting structure.

The above explanations are the basis for a linear programming model in which the goal is to increase organizational effectiveness or to achieve the final goals of the organization through repeated organizational activities, which are limited to the amount of various cost drivers using resources. This model is presented in Section 3.2 as the main model of the study.

To estimate the parameters of the model, we developed an Artificial Neural Network. We use a linear ANN model to estimate the value of cost drivers and future costs. The inputs of the network are the volume of activities, and the outputs are different types of costs. After training and validating the ANN, we used the model weights as cost drivers. This model is presented in Section 3.3.

Finally, we propose two linear programming models with a robust approach. We use the Soyster and Bertsimas&Sym models to develop robust counterparts of the main PBB model.

3.2. Linear programming model for performance based budgeting

Linear programming for PBB, based on the definition mentioned in Section 3.1, is as follows:

$$\text{Maximize } \sum_{r=1}^n \sum_{q=1}^Q \sum_{p=1}^P \sum_{k=1}^K e_{qr} d_{pq} c_{kp} I_k z_k$$

Subject to:

$$\sum_{i=1}^m \sum_{j=1}^n a_{ij} x_j \leq \left(\sum_{i=1}^m \sum_{j=1}^n a_{ij} \right) S'_i / S_i$$

$$\sum_{j=1}^n b_{jk} x_j \geq z_k; k=1, \dots, n$$

Boundary constraints

$$x_j, z_k \geq 0; x_j, z_k \in Z \quad \forall i, k, j$$

In this model, the structure of planning, performance evaluation, costing, and resource constraints are considered simultaneously. Objective function coefficients are related to the performance score of activities, products, programs, and goals ; resource coefficients are cost drivers ; and variables include the volume of activities and the number of products produced. This model is different from all budgeting models because its main variable type is not cash, but rather performance (volume of activity), and their coefficients are formed from drivers, not utilities. In Section 3.2.1, we describe the variables and indices of this model. In 3.2.2 the objective function is explained and in 3.2.3 we describe the constraints of the model.

3.2.1. Variables

The variables and indices are defined as follows:

Indices: Long term goal indices: $r = 1, 2, \dots, R$, short term goal indices: $q = 1, 2, \dots, Q$, action plan indices: $p = 1, 2, \dots, P$, output(product) indices: $k = 1, 2, \dots, K$, activity indices : $j = 1, 2, \dots, m$, resource indices: $i = 1, 2, \dots, n$.

Variables :Volume of activity j: x_j , Volume of output(product) k: z_k , cost driver of resource(cost) i in return of activity j: a_{ij} , activity driver of activity j in return of output k: b_{jk} ,

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3.2.2. Objective function

In this model, the objective function is to maximize the effectiveness of performance(long-term goal achievements). Long-term goal achievement is measured using performance scores and different performance indicators. According to the structure shown in Fig. 1, the long-term goal performance score is equal to the short-term goal score multiplied by their weights in long-term goals(short-term goal drivers).In this model, we use drivers instead of weights because the driver value shows the weight of influence of one item on the other. The short-term goals performance score is also equal to the action plan score multiplied by the action plan drivers, and the action plan performance score is equal to the performance score of the output multiplied by the output driver. The performance score of each output was evaluated using performance evaluators. Therefore, after replacement, we will have the following phrase showing the organizational long-term goal performance score, and according to performance-based budgeting literature, we expect its increase.

$$\sum_{r=1}^n \sum_{q=1}^Q \sum_{p=1}^P \sum_{k=1}^K e_{qr} d_{pq} c_{kp} I_k z_k$$

3.2.3. Constraints

In this model, constraints refer to the restriction of the available resources. Activities use various organizational resources (human resources, equipment, energy, and materials). The use of each activity from any resource is recognized as a cost (resource) driver, which forms variable coefficients in constraint 1. In budgeting, we expect each resource (in return for performing each activity) to be equal to the predicted value or less, so the first constraint is formed. The right-hand side of the first-row constraint refers to the estimated value of resources for the future.

The second-row constraint is presented to create a balance and logical relation among different levels of the budgeting structure, as shown in Fig. 1. For example, the production of a particular output in an organization requires a certain volume of different activities; therefore, it should be considered as the second constraint.

Boundary constraints are used to restrict variables if necessary.

The last row of the constraints shows that the proposed model is an integer programming type (the volume of each activity and output is an integer) and prevents them from obtaining a zero value.

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After solving the model and determining the optimum volume of activities and the number of outputs, the following cases were extracted from the model. The description of the Variables and Indexes is presented in Table 2.

$$\text{Activity budget} = \frac{(\sum_{i=1}^m \sum_{j=1}^n S_i a_{ij} x_j)}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}}$$

$$\text{Product budget} = \frac{(\sum_{k=1}^K \sum_{i=1}^m \sum_{j=1}^n S_i b_{jk} a_{ij} x_j)}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}}$$

$$\text{Action plan budget} = \frac{(\sum_{p=1}^P \sum_{k=1}^K \sum_{i=1}^m \sum_{j=1}^n S_i C_{kp} b_{jk} a_{ij} x_j)}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}}$$

$$\text{Short term goal budget} = \frac{(\sum_{q=1}^Q \sum_{p=1}^P \sum_{k=1}^K \sum_{i=1}^m \sum_{j=1}^n S_i d_{pq} c_{kp} b_{jk} a_{ij} x_j)}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}}$$

$$\text{Long term goal budget} = \frac{(\sum_{r=1}^R \sum_{q=1}^Q \sum_{p=1}^P \sum_{k=1}^K \sum_{i=1}^m \sum_{j=1}^n S_i e_{qr} d_{pq} c_{kp} b_{jk} a_{ij} x_j)}{\sum_{i=1}^m \sum_{j=1}^n a_{ij}}$$

Table 2.

Description of variables and indices.

Level	Index/Variable	Description	Driver / Weight
Long-term Goal	r	Strategic organizational objectives	Short-term goal drivers (st_{qr})
Short-term Goal	q	Tactical objectives contributing to long-term goals	Action plan drivers (ap_{pq})
Action Plan	p	Specific programs/projects to achieve short-term goals	Output drivers (ok_p)
Output / Product	k	Measurable deliverables or products	Activity drivers (a_{qr})
Activity	j	Operational tasks or work packages	Resource cost drivers (c_{ij})
Resource	i	Human, material, equipment, energy, etc.	Estimated cost (\hat{R}_i)

3.3. Using artificial neural network for cost estimation relationship

A critical challenge in performance-based budgeting (PBB) is accurately estimating the relationship between organizational activities and associated costs. This requires the definition of a robust cost function capable of predicting future expenditures for each activity or output. The proper estimation of this cost function is essential, as inaccuracies can propagate through resource

allocation, budgeting, and performance evaluation, potentially undermining the effectiveness of the budget.

In recent years, researchers have increasingly employed Artificial Neural Networks (ANNs) to model complex nonlinear cost behaviors, especially in contexts where cost drivers are many and interdependent ([Bodendorf et al., 2021](#); [Matel et al., 2019](#)). ANNs can approximate arbitrary cost and production functions, offering flexibility beyond traditional parametric approaches ([He et al., 2025](#)). They have also been shown to produce accurate cost estimates for engineering services based on limited project-level data ([Matel et al., 2019](#)).

Moreover, hybrid and advanced machine learning approaches have gained traction. Systematic reviews show that methods such as ANNs, ensemble learning, and gradient-boosted trees often outperform traditional regression for cost estimation tasks across domains, including construction and healthcare ([Hashemi et al., 2020](#); [Shamim et al., 2025](#)). For instance, combining ANN with optimization techniques can identify optimal network architectures and select the most influential cost drivers, thereby minimizing the prediction errors ([Bodendorf et al., 2021](#)).

In practical implementation within a PBB framework, organizational activity volumes can be treated as input features for an ANN to estimate the corresponding resource costs as outputs ([Matel et al., 2019](#)). Such a data-driven cost function captures nonlinear effects, interactions among cost drivers, and indirect relationships that traditional linear models may overlook. Once trained, the network's learned weights effectively act as cost coefficients (or "derivatives") that can be integrated into optimization or budgeting tools (e.g., linear or nonlinear programming models). This integration enables decision-makers to link predicted costs directly with performance outputs, facilitating more accurate, adaptive, and transparent budgeting in dynamic organizational environments ([Hashemi et al., 2020](#); [Shamim et al., 2025](#)).

However, it is important to note that ANNs are not always the optimal approach. In comparative studies, other machine learning techniques have sometimes outperformed ANNs, depending on the data quality, features, and problem structure ([Bodendorf et al., 2021](#); [Shamim et al., 2025](#)). Therefore, while ANN-based frameworks hold great promise for cost estimation in PBB contexts, their application should be accompanied by careful selection of input variables, proper preprocessing (e.g., feature selection and normalization), and validation (e.g., cross-validation and out-of-sample testing), potentially in combination with other ML or hybrid methods to achieve the best results.

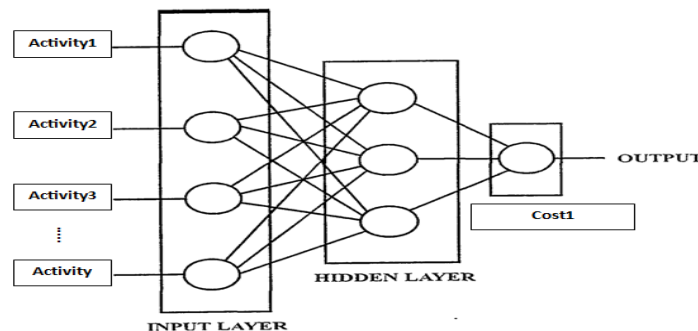


Fig. 1. Architecture of the ANN model.**3.4. Robust counterpart of the proposed model (according to Soyster's Model)**

As mentioned in Section 2.2, robust models are used when there are uncertain parameters in the model. In this case, the feasibility and optimality of the issue may be endangered even by changing one parameter. The uncertain parameters of the proposed model are the coefficient of the objective function and constraints (values of drivers) and the predicted value for costs (right-hand side of constraints). As discussed in Section 3.2, in our model, the future value of cost drivers and costs are extracted from an ANN; therefore, they may be less or more in practice. This issue highlights the importance of presenting a robust model for budgeting. The purpose of creating a robust PBB model is to perform budgeting in a way that preserves the feasibility and optimality of the solution. These models can also lead to a more flexible budget. The robust counterpart of the proposed model based on Oyster's model is as follows:

$$\text{Max} \sum_{r=1}^n \sum_{q=1}^Q \sum_{p=1}^P \sum_{k=1}^K e_{qr} d_{pq} c_{kp} I_k z_k$$

St:

$$\sum_{i=1}^m \sum_{j=1}^n a_{ij} x_j - \hat{S}_i y \leq \left(\sum_{i=1}^m \sum_{j=1}^n a_{ij} \right) S_i' m_i / S_i \quad \forall_i, S_i \in U \quad \text{Uncertainty set : } U$$

$$-y \leq m_i \leq y$$

$$\sum_{j=1}^n b_{jk} x_j \geq z_k \quad ; k=1, \dots, n$$

Boundary Constraints

$$y, m_i, x_j, z_k \geq 0; x_j, z_k \in Z \quad \forall i, k, j$$

$$\text{That: } \forall_i : S_i \in [S_i - \hat{S}_i, S_i + \hat{S}_i]$$

Performance based budgeting robust counterpart model (according to Bertsimas and Sym's model)

The robust counterpart of the proposed model based on Bertsimas and Sym's model is as follows:

$$\text{Max} \sum_{r=1}^n \sum_{q=1}^Q \sum_{p=1}^P \sum_{k=1}^K e_{qr} d_{pq} c_{kp} I_k z_k - g_0 \Gamma_0 - \sum_j p_{0j}$$

Subject to:

$$\sum_k \sum_j \sum_i a_{ij} x_{jk} - z_i \Gamma_i + \sum_{j \in J_i} p_{ij} \leq S_i \quad \forall i$$

$$\sum_{j=1}^n b_{jk} x_j \geq z_k \quad ;k=1,...,n$$

$$g_0 + p_{0j} \geq d'_j y_j \quad \forall j \in J_0$$

$$g_i + p_{ij} \geq \hat{a}_{ij} y_j \quad \forall i \neq 0, j \in J_i$$

$$x_j, z_k \geq 0; x_j, z_k \in Z \quad \forall i, k, j; 0 \leq a, b, c, d, e, I \leq 1 \quad p_{ij} \geq 0, \forall i \quad g_i \geq 0, \forall j \quad y_j \geq 0, \forall i, j \in J_i$$

$$\forall j - y_j \leq x_j \leq y_j, k$$

In this model:

$$\Gamma_i \in [0,1], c_{kp} \in [c_{kp} - c'_{kp}, c_{kp}], b_{jk} \in [b_{jk} - b'_{jk}, b_{jk}], a_{jk} \in [a_{jk} - \hat{a}_{jk}, a_{jk} + \hat{a}_{jk}], \\ e_{kp} \in [e_{kp} - e'_{kp}, e_{kp}], d_{pq} \in [d_{pq} - d'_{pq}, d_{pq}]$$

4. Data

To test the presented models in a corporate environment, we chose Tejarat Bank of Iran. The managers of this bank intend to apply PBB for budgeting because they believe that this method can better allocate their indirect costs. They conducted an ABC project to determine the final price of their product as a prerequisite for PBB. We used the information of four-year planning, costing, budgeting, and performance evaluation of this bank to test the models. First, a field of operation in the bank (departments of financial resource allocation) is selected, and then the necessary information, such as important activities of the field, bank services (outputs of plans), action plans, short-term and long-term goals, and relationships between them, are gathered. To extract logical relations and evaluate products, action plans, goal drivers, and bank experts' views were used. These relations are as follows: the relations between activities and costs, activities and services (outputs), services and action plans, action plans and short-term goals, and short-term and long-term goals. An ANN was used to extract the values of the cost drivers. In addition, the annual results of the performance evaluation for the selected activities and outputs were used as a key performance indicator that was multiplied by the coefficient of the objective function. To have a brief model, we did not use a long hierarchy of planning. A number of activities, services, and action plans are chosen, and only one long-term goal of the bank is considered.

4.1. Information gathering

To collect information and achieve a long-term goal, a number of activities, services, and action plans were selected, which are presented in table1. The most important data of the bank that we used were the number of products, the amount of different types of costs, the value of activity and product drivers, and the annual performance score of the activity for four years.

Table 3.

Selected activities, outputs, and action plans of Tejarat Bank.

R. H.S	Resource Name (Cost)	Variable Name	Activity Name	Variable Name	Output	Index	Action Plan	Short Term Goal	Long Term Goal
S1	-Personnel	x1	-Resource	z1	Mozarebeh(	p1	10 percent	gaining	Increasing
S2	Costs	x2	allocation	z2	One kind of		Increase in	profit	g the net
S2	-	x3	policy		Islamic		payment	by	profit of
S4	Administrat	x4	-Customer		Banking		of	keeping	Tejarat
S5	ion Costs	x5	evaluation		services)		participato	current	bank
	-Energy	x6	(foreign &		Civil		ry	incomes	
	-	x7	domestic		participatio		facilities	of	
	Information	x8	currency)		n(One kind			departm	
	and		-Issuance		of Islamic			ents of	
	communica		and		Banking			financia	
	tion costs		announceme		services)			l	
	-		nt of the	z3	futures	P2	15 percent	resource	
	Consumabl		enactments	z4	Installment		Increase in	allocati	
	e material		-Resource	z5	contracts		payment	on	
	costs		Allocation	z6	Leasing		of		
			Spending		Bank		exchange	facilities	
			Supervision		commitmen				
			on		t				
			-Credit		purchase(O				
			facilities		ne kind of				
			payment		Islamic				
			-Refunding		Banking				
			and		services)				
			liquidation	z7	Private	P3	10 percent		
			of facilities	z8	foreign		Increase in		
			-Issuing,		exchange		payment		
			extending,		facilities		of foreign		
			liquidation		Government		facilities		
			and		tal foreign				
			cancellation		exchange				
			of		facilities				
			guarantees	z9	interest-free	P4	12 percent		
			and	z10	loan		Increase in		
			liabilities	z11	facilities		sale of		
			-Liabilities		Letter of		domestic		
			collection		guarantee		and		
					Documentar		foreign		
					y letter of		commitme		
					credit		nt		

4.2. Artificial neural network model for estimating cost drivers

4.2.1 Artificial Neural Network Model for Estimating Cost Coefficients

A multilayer feedforward ANN was implemented to estimate the cost coefficients associated with banking activities, a multilayer feedforward artificial neural network (ANN) was implemented. The input layer comprised activity rates (operational volumes), and the output layer represented various cost categories ([Bodendorf et al., 2021](#); [Kim & Han, 2003](#); [Matel et al., 2019](#)). Financial records detailing costs and the number of banking services delivered were collected weekly for four years. Activity rates were computed based on the observed relationships between the activities and outputs (Table 2).

4.2.2. Network Architecture and Activation Functions

The ANN consisted of 2–3 hidden layers, with the number of neurons in each layer optimized through iterative experimentation. The output layer employs a linear (pure-linear) activation function to accurately model approximately linear input-output relationships. The hidden layers utilized ReLU and Sigmoid activation functions to capture nonlinear patterns and complex interactions among the cost drivers.

4.2.3. Data Preprocessing and Dataset Partitioning

Prior to training, all the input data were standardized to ensure uniform scales and promote stable convergence. The dataset was divided as follows.

- 60% for training
- 20% for validation during training
- 20% held out for testing the network's generalization performance

This partitioning, in combination with early stopping and dropout regularization, effectively mitigated overfitting and enhanced the robustness of the model.

4.2.4. Training Procedure and Optimization

The network was trained using a backpropagation algorithm with a learning rate of 0.1 and a momentum coefficient of 0.1. The initial weights were set to 0.3. Training was conducted using 50,000 and 100,000 training patterns to identify the configuration that minimized the Mean Absolute Percentage Error (MAPE) on the holdout data. Training and validation sets were employed for weight optimization and model fitting, whereas the holdout set was used to evaluate the predictive performance on unseen data.

4.2.5. Performance Metrics

Model performance was assessed using MAPE, Root Mean Square Error (RMSE), and coefficient of determination (R^2) to ensure a comprehensive evaluation of prediction accuracy. The ANN with three hidden layers and 50,000 training patterns achieved the best results, attaining a MAPE of 1.235% for the holdout data.

4.2.6. Sensitivity Analysis and Identification of Key Cost Drivers

A sensitivity analysis was conducted based on the trained network weights to quantify the contribution of each activity to the total cost. The analysis revealed that activities such as guarantee issuance, renewal, and loan repayments exerted the greatest influence on overall costs. These findings highlight the ability of ANN to identify critical cost drivers in a data-driven manner.

4.2.7. Advantages of ANN for Cost Coefficient Estimation

- Nonlinear modeling of complex interactions: ANN capture intricate relationships among cost drivers that are often undetectable by traditional linear models.
- High generalizability: Strong performance on holdout data indicates reliable predictive capabilities for future cost estimations.

- Dynamic adaptability: The network can update the weights and coefficients with new data, improving the responsiveness to changes in activity levels and outputs.
- Data-driven cost coefficients: Trained weights provide realistic cost coefficients that can be used to inform resource allocation and budgeting decisions.

A summary of the model performance is presented in Table and Fig. 3.

Table 4.

Ann performance summary table.

Hidden Layers	Training Patterns	Training MAPE	Holdout MAPE
2	50,000	0.882%	1.245%
2	100,000	0.892%	1.289%
3	50,000	0.840%	1.235%
3	100,000	0.861%	1.266%

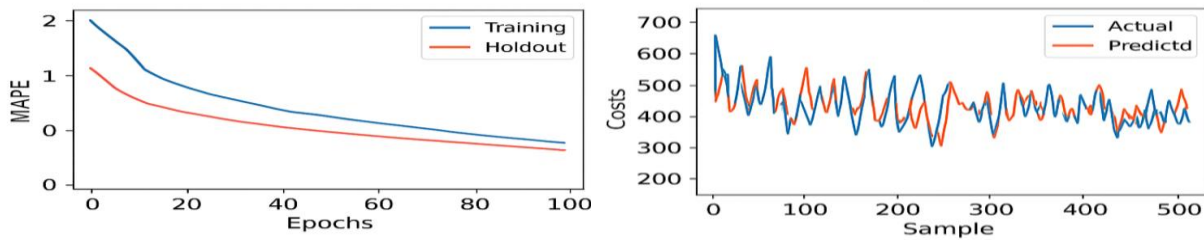


Fig. 3. Model performance.

5. Experimental analysis

With respect to the variable coefficients extracted from ANN and the right-hand side of the constraint's quantities, and based on the deterministic model of linear programming for performance-based budgeting represented in Section 3.2, the performance-based budgeting model in one of Tejarat Bank is defined as follows:

$$\text{Max } 0.25 z_1 + 0.13 z_2 + 0.35 z_3 + 0.43 z_4 + 0.15 z_6 + 0.44 z_6 + 0.09 z_7 + 0.15 z_8 + 0.22 z_9 + 0.14 z_{10} + 0.72 z_{11}$$

SUBJECT TO

$$5x_1 + 5x_2 + x_3 + 15x_4 + 2x_5 + x_6 + x_7 + 15x_8 + x_9 \leq 2674$$

$$3x_1 + 15x_2 + x_3 + x_4 + 2x_5 + x_6 + 5x_7 + 5x_8 + x_9 \leq 3346$$

$$5x_1 + 5x_2 + 15x_3 + x_4 + x_5 + 2x_6 + 15x_7 + x_8 + 2x_9 \leq 5689$$

$$15x_1 + x_2 + x_3 + x_4 + 2x_5 + x_6 + 5x_7 + 15x_8 + x_9 \leq 4500 \quad 15x_1 + x_2 + 5x_3 + 5x_4 + 2x_5 + x_6 + 3x_7 + 15x_8 + 6x_9 \leq 3456$$

$$5x_1 + 5x_2 + 15x_3 + x_4 + x_5 + 2x_6 + 15x_7 + x_8 + 2x_9 \leq 2459$$

$$15x_1 + x_2 + x_3 + x_4 + 2x_5 + x_6 + 5x_7 + 15x_8 + x_9 \leq 5677$$

$$15x_1 + x_2 + 5x_3 + 5x_4 + 2x_5 + x_6 + 3x_7 + 15x_8 + 6x_9 \leq 3456 \quad 3x_1 + 2x_2 + 5x_3 + x_4 + 8x_5 + 6x_6 + 2x_7 + 5x_8 + x_9 -$$

$$z_1 > \quad = \quad 0 \quad x_1 + x_2 + 3x_3 + 5x_4 + 2x_5 + 7x_6 + 4x_7 + x_8 + 8x_9 - z_2 > \quad = \quad 0$$

$$\begin{aligned}
3x_1+2x_2+5x_3+7x_4+6x_5+8x_6+x_7+9x_8+9x_9-z_3 &>= 0 & 3x_1+x_2+3x_3+2x_4+x_5+2x_6+5x_7+3x_8+5x_9- \\
z_4 &= 0 & 5x_1+3x_2+5x_3+3x_4+x_5+5x_6+7x_7+x_8+8x_9-z_5 &= 0 \\
4x_1+x_2+x_3+4x_4+2x_5+8x_6+4x_7+7x_8+8x_9-z_6 &>= 0 & 5x_1+4x_2+1x_3+7x_4+4x_5+8x_6+2x_7+5x_8+3x_9- \\
z_7 &= 0 & 7x_1+2x_2+2x_3+4x_4+2x_5+3x_6+x_7+8x_8+x_9-z_8 &= 0 \\
3x_1+7x_2+4x_3+3x_4+2x_5+8x_6+1x_7+5x_8+7x_9-z_9 &>= 0 & 3x_1+2x_2+4x_3+x_4+2x_5+6x_6+2x_7+2x_8+x_9- \\
z_{10} &>= 0 & x_1+7x_2+5x_3+x_4+8x_5+x_6+2x_7+3x_8+7x_9-z_{11} &>= 0
\end{aligned}$$

$$\begin{aligned}
x_1 &>= 10, x_2 >= 10, x_3 >= 10, x_4 >= 10, x_5 >= 10, x_6 >= 10, x_7 >= 10, x_8 >= 10, x_9 >= 10, z_1 >= 0, z_2 >= \\
0, z_3 >= 0, z_4 >= 0, z_5 >= 0, z_6 >= 0, z_7 >= 0, z_8 >= 0, z_9 >= 0, z_{10} >= 0, z_{11} >= 0
\end{aligned}$$

$$x_1 - x_9; z_1 - z_{11} \in \mathbb{Z}$$

END

As mentioned in Section 3.3, uncertain conditions in budgeting parameters, such as available resources in the future budgeting period or variable coefficients in constraints and objective functions (deriver values, performance indicator weights), can lead to a loss of optimality and inefficiency of the presented deterministic model. Therefore, the robust counterpart of performance-based budgeting in banks with respect to the proposed model is described as follows: For a set of uncertainty exploitations, we used bank experts' views and referred to prior-period data. We considered uncertain quantities for high level boundary between 90 %and 110% and for low level boundary between 50 %and 70%. To solve the model with Soyster and Bertsimas's method, aiming at determining the level of conservativeness in the objective function and constraints, it was necessary to first obtain the number of uncertain parameters. According to Number of uncertain parameters = (n*m) +m ([Bertsimas & Sym, 2004](#))

We have (11 × 9)+11 equal to 110 uncertain parameters. Therefore, the conservative level of the objective function is between 0 and 110, and the constraint conservation level changes between 0 and 1 according to the definitions.

In continuation, a performance-based budgeting robust model in Tejarat Bank is represented.

$$\text{Max } 0.26 z_1 + 0.03 z_2 + 0.05 z_3 + 0.03 z_4 + 0.05 z_6 + .09z_7+0.15z_8+0.02z_9+0.04z_{10}+0.12z_{11}$$

Subject to

$$5x_1+5x_2+x_3+15x_4+2x_5+x_6+x_7+15x_8+x_9-200y-1000m_1 \leq 0$$

$$x_1+15x_2+x_3+x_4+2x_5+x_6+5x_7+5x_8+x_9-200y-1000m_2 \leq 0$$

$$5x_1+5x_2+15x_3+x_4+x_5+2x_6+15x_7+x_8+2x_9-200y-1000m_3 \leq 0$$

$$15x_1+x_2+x_3+x_4+2x_5+x_6+5x_7+15x_8+x_9-200y-1000m_4 \leq 0$$

$$15x_1+x_2+5x_3+5x_4+2x_5+x_6+3x_7+15x_8+6x_9-200y-1000m_5 \leq 0$$

$$3x_1+2x_2+5x_3+x_4+8x_5+6x_6+2x_7+5x_8+x_9-z_1 >= 0$$

$$x_1+x_2+3x_3+5x_4+2x_5+7x_6+4x_7+x_8+8x_9-z_2 >= 0$$

$$3x_1+2x_2+5x_3+7x_4+6x_5+8x_6+x_7+9x_8+9x_9-z_3 \geq 0$$

$$3x_1+x_2+3x_3+2x_4+x_5+2x_6+5x_7+3x_8+5x_9-z_4 \geq 0$$

$$5x_1+3x_2+5x_3+3x_4+x_5+5x_6+7x_7+x_8+8x_9-z_5 \geq 0$$

$$4x_1+x_2+x_3+4x_4+2x_5+8x_6+4x_7+7x_8+8x_9-z_6 \geq 0$$

$$5x_1+4x_2+1x_3+7x_4+4x_5+8x_6+2x_7+5x_8+3x_9-z_7 \geq 0$$

$$7x_1+2x_2+2x_3+4x_4+2x_5+3x_6+x_7+8x_8+x_9-z_8 \geq 0$$

$$3x_1+7x_2+4x_3+3x_4+2x_5+8x_6+1x_7+5x_8+7x_9-z_9 \geq 0$$

$$3x_1+2x_2+4x_3+x_4+2x_5+6x_6+2x_7+2x_8+x_9-z_{10} \geq 0$$

$$x_1+7x_2+5x_3+x_4+8x_5+x_6+2x_7+3x_8+7x_9-z_{11} \geq 0$$

$$m_1-y \leq 0, m_1+y \geq 0, m_2-y \leq 0, m_2+y \geq 0, m_3-y \leq 0, m_3+y \geq p, m_4-y \leq 0, m_4+y \geq 0, m_5-y \leq 0, m_5+y \geq 0, x_1 \geq 10, x_2 \geq 10, x_3 \geq 10, x_4 \geq 10, x_5 \geq 10, x_6 \geq 10, x_7 \geq 10, x_8 \geq 10, x_9 \geq 10, z_1 \geq 0, z_2 \geq 0, z_3 \geq 0, z_4 \geq 0, z_5 \geq 0, z_6 \geq 0, z_7 \geq 0, z_8 \geq 0, z_9 \geq 0, z_{10} \geq 0, z_{11} \geq 0, m_1 \geq 0, m_2 \geq 0, m_3 \geq 0, m_4 \geq 0, m_5 \geq 0, y \geq 0, X_1 - x^q \text{ \& } z_1 - z_{11} \in Z$$

6. Results

We developed 14 models of budgeting for each of the four years (one deterministic model, one robust model based on Soyster's model, and 12 models based on Bertsimas&sym's model). With respect to the collected data described in Section 4, the existing models were programmed using Lingo software and then solved. The final results are presented in Table 4.6. The budget is calculated based on the formulas presented in Section 3.2.3. Table 6 shows the results of testing different conservatism levels of the coefficients of constraints and objective function of Bertsimas &sym. The results showed a higher decrease in the objective function value in return for higher conservatism levels. We compared the results of each model with the real costs for each year separately. We used the indicator of budget deviation of action plans to compare the results of the models.

$$(\text{Allocated budget} - \text{real cost})/\text{real cost}$$

As shown in Table 6, this indicator improved using robust models. The result of the application of the Bertsimas and Sym model also showed that an increase in the level of conservatism of the objective function and constraint coefficients will improve the indicator of budget deviation. However, this indicator should be considered simultaneously with the objective function reduction level presented in Table 6.

Table 5.

Optimum volume and allocated budget of activities and outputs based on the soyster model.

Variable name	Activity name	Optimum value	Budget
X1	Resource allocation policy	100	124567
X2	Customer feasibility(Foreign exchange and cash)	122	45789
X3	Issuance and announcement of the enactment	103	23456
X4	Resource allocation consumption control	10	43678
X5	Facilities	146	56788
X6	Re-paying and facilities adjustment	206	45789
X7	Issuing, extending, adjusting and canceling commitments and guarantee letters	167	67890
X8	Tracing and collecting demands	10	66789
Z1	Circulation	2603	26489
Z2	Civil participation	1970	34900
Z3	Precedor purchase	2893	45000
Z4	Installment sale	780	24555
Z5	Leasing	0	33789
Z6	Bank commitment purchase	2236	34344
Z7	Private foreign exchange facilities	2510	50077
Z8	Governmental foreign exchange facilities	1163	45666
Z9	interest-free loan facilities	2246	56888
Z10	Guarantee	1683	34678
Z11	Documentary credits	1640	15688

Table 6.

Allocated budget for action plans and goals based on the soyster's model.

Variable Name	Action Plan	Predicted Budget
P1	10 Percent Increase In Payment Of Participatory Facilities	77712694
P2	15 Percent Increase In Payment Of Exchange Facilities	226168978
P3	10 Percent Increase In Payment Of Foreign Facilities	178818051
P4	12 Percent Increase In Domestic And Foreign Commitment	211911332
SG	Gaining Profit By Keeping Current Incomes Of Departments Of Financial Resource Allocation	۸۴۷۶۴۵۳۲
LG	Increasing The Net Profit Of Tejarat Bank	۶۷۸۱۱۶۲۶

Table 7.

Results of comparing the allocated budget and the real cost of each year.

Model	Budget Deviation For Year 1	Budget Deviation For Year 2	Budget Deviation For Year 3	Budget Deviation For Year 4	AVG
Deterministic Model	0.12	0.22	0.08	0.16	0.15
Robust Model (Soyster)	0.1	0.09	0.08	0.13	0.10

Model		Budget Deviation For Year 1	Budget Deviation For Year 2	Budget Deviation For Year 3	Budget Deviation For Year 4	AVG		
	Objective Function's Conservatis m Level	Constrain t 'S Conservat ism Level	Objective Function Reduction (Percent)	Budget Deviatio n For Year 1	Budget Deviatio n For Year 2	Budget Deviatio n For Year 3	Budget Deviatio n For Year 4	AVG
Robust Model (Bertsimas And Sym)	0	0	0	0.12	0.22	0.18	0.16	0.17
	0.1	0.1	0.027	0.12	0.18	0.15	0.15	0.15
	0.1	0.1	0.047	0.11	0.16	0.15	0.14	0.14
	0.2	0.2	0.279	0.11	0.15	0.13	0.14	0.13
	0.3	0.3	0.301	0.1	0.14	0.12	0.13	0.12
	0.4	0.4	0.356	0.09	0.12	0.11	0.12	0.11
	0.5	0.5	0.435	0.08	0.12	0.09	0.11	0.10
	0.6	0.6	0.472	0.07	0.09	0.06	0.09	0.08
	0.7	0.7	0.479	0.07	0.09	0.06	0.09	0.08
	0.8	0.8	0.496	0.06	0.08	0.06	0.09	0.07
	0.9	100	0.501	0.06	0.07	0.05	0.07	0.06
	1	110	0.51	0.05	0.05	0.04	0.06	0.05

7. Conclusion

In recent years, the organizational adoption of performance-based budgeting (PBB) has gained renewed attention, particularly within the framework of smart governance, which demands decision-making that is transparent, accountable, data-driven, and resilient to uncertainties. This study introduces a hybrid framework that responds to this call by integrating Artificial Neural Networks (ANNs) with robust linear optimization. The ANN component provides a powerful data-driven method for accurately estimating cost coefficients and predicting future costs, moving beyond traditional subjective estimates. These predictions were then fed into robust optimization models, specifically those of Soyster and Bertsimas–Sim, to ensure that budget allocations remained both optimal and feasible under real-world uncertainties.

Empirical validation using a four-year dataset from an Iranian bank demonstrates the practical efficacy of this approach. The implementation of Soyster's robust optimization framework resulted in a 30% reduction in the objective function value compared to a deterministic model, whereas allocations to action plans showed greater stability with variations of approximately $\pm 10\%$. The application of Bertsimas and Sim's approach further refined these outcomes, illustrating a clear trade-off: by systematically increasing the conservatism parameter, budget reliability improved significantly, as measured by a markedly enhanced budget deviation indicator. This provides decision-makers with a powerful lever to balance performance ambitions and risk tolerance.

However, the journey toward truly smart governance requires addressing a critical challenge inherent in our model: the "black-box" nature of ANNs. Although they offer superior predictive accuracy, their lack of inherent transparency can conflict with the core governance principle of accountability. Therefore, the full potential of this AI-enabled framework is unlocked only when it is augmented with Explainable AI (XAI) techniques, such as SHAP or LIME. These tools can illuminate the reasoning behind ANN's cost predictions, explaining which activity drivers most influence each cost estimate. This transforms the model from a purely technical tool into a

transparent and justifiable decision support system. When combined with the intrinsic transparency of the optimization model's logic, where the allocation of resources is directly linked to explicit performance goals and constraints, the entire framework becomes a robust foundation for accountable, data-driven governance.

These findings demonstrate that the synergy of ANN's predictive power of ANN and the resilience of robust optimization forms a solid foundation for intelligent fiscal management. It enables organizations to allocate resources more efficiently, anticipate financial uncertainties, and build responsive and accountable budgeting systems.

We recommend two primary directions for future research. First, to enhance transparency, XAI methodologies should be integrated into AI-enabled PBB models. Second, to handle deeper uncertainties, the development of robust PBB models incorporating fuzzy logic can simultaneously address numerical uncertainty and linguistic ambiguity in budgeting variables. Additionally, exploring nonlinear performance-based budgeting models could further improve predictive accuracy and resource optimization, thereby strengthening the foundations of smart governance across both public and private sectors

Acknowledgements

The authors sincerely thank the anonymous reviewers for their valuable comments and constructive suggestions, which significantly improved the quality of this study.

Funding Statement

This study received no external funding.

Conflicts of interest

The authors declare no conflicts of interest.

Authors contribution statement

All authors have approved the final statement.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable requests.

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